Pest Classification and Pesticide Recommendation System

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ABSTRACT

Myanmar is an agricultural country and agriculture constitutes the largest sector of the economy. Recognizing of pests is a vital problem especially for farmers, agricultural researchers, and environmentalists. The proposed system is to classify the types of pest using the CNN model, which is often used when applying deep learning to image processing, and to recommend the most suitable pesticide according to the type of pest. This system will help to know easily information of pests and pesticides which should be used to the user. Using a public dataset of 1265 images of pests, a convolutional network and supervised methods are trained to classify four kinds of pest species and recommend the suitable pesticides.

KEYWORDS: CNN

INTRODUCTION

Agriculture not only provides food for the human existence but also a big source for the economy of any country. In agriculture, pest control has always been considered as the most challenging task for farmers. Most of the farmers used the traditional pest management methods which is the regular spray program based on schedules rather than the presence of insect pests on the paddy fields. Insects and pests damage the crops and, thus, are very dangerous for the overall growth of the crop. So, there is a need to detect these pests at all stages of their lifecycle: One method to protect the crop is early pest detection so that the crop can be protected from pests' attack. If useful pests are detected, appropriate measures can be taken to protect the crop from a big production loss at the end.

Early detection would be helpful for minimizing the usage of the pesticides and would provide guidance for the selection of the pesticides. Early detection of the pests in crops is a major challenge facing farmers during these days. Manual examination of wide crop fields is very time consuming and less effective. It also requires availability of experts, so it becomes a very costly activity. Automation of pest recognition is an important process for the fields working with pests.

A. Convolutional Neural Network

A convolutional neural network is an artificial neural network that presents a sparse connectivity, on biological inspiration, and it is applied with success in many computer vision problems. In the classification problem, the structure of a convolutional neural network is the series of computational blocks (or layers) stacking together and ending with a classifier, Convolutional neural networks (CNNs) have become popular especially in computer vision in the last few years because of outstanding performance on different tasks, such as image classifications. Convolutional Networks are a category of Neural Networks that have proven very effective in areas such as image recognition and classification.

B. CNN Architecture

➤ LeNet-5, a pioneering 7-level convolutional network by LeCun et al in 1998, that classifies digits, was applied by several banks to recognize hand-written numbers on checks digitized in 32x32 pixel greyscale input images. The ability to process higher resolution images requires larger and more convolutional layers, so this technique is constrained by the availability of computing resources.

➤ AlexNet significantly outperformed all the prior competitors and won the challenge by reducing the top-5 error from 26% to 15.3%. The second place top-5 error rate, which was not a CNN variation, was around 26.2%. The network had a very similar architecture as LeNet by Yann LeCun et al but was deeper, with more filters per layer, and with stacked convolutional layers. It consisted 11x11, 5x5,3x3, convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum.

➤ The winner of the ILSVRC 2014 competition was GoogLeNet (a.k.a. Inception V1) from Google. It achieved a top-5 error rate of 6.67%! This was very close to human level performance which the organizers of the challenge were now forced to evaluate. As it turns out, this was actually rather hard to do and required some human training in order to beat GoogLeNet accuracy. After a few days of training, the human expert (Andrej Karpathy) was able to achieve a top-5 error rate of 5.1%(single model) and 3.6%(ensemble). The network used CNN inspired by LeNet but implemented a novel element which is dubbed an inception module. It used batch normalization, image distortions and RMSprop. This module is based on several very small convolutions in order to drastically reduce the number of parameters. Their architecture consisted of a 22-layer deep CNN but

reduced the number of parameters from 60 million (AlexNet) to 4 million.

➢ ILSVRC 2013 winner was also CNN which became known as ZFNet. It achieved a top-5 error rate of 14.8% which is now already half of the prior mentioned non-neural error rate. It was mostly an achievement by tweaking the hyper-parameters of AlexNet while maintaining the same structure with additional Deep Learning elements.

➢ AlexNet has parallel two CNN line trained on two GPUs with cross-connections, GoogLeNet has inception modules, ResNet has residual connections. At the ILSVRC 2015, the so called Residual Neural Network (ResNet) by Kaiming He et al introduced anovel architecture with "skip connections" and features heavy batch normalization. Such skip connections are also known as gated units or gated recurrent units and have a strong similarity to recent successful elements applied in RNNs. Because of this technique, it is possible to train a NN with 152 layers while still having lower complexity than VGGNet. It achieves a top-5 error rate of 3.57% which beats human-level performance on this dataset.

C. GoogLeNet/Inception
By the "GoogLeNet" name, it will be referred to the particular incarnation of the Inception architecture used for the ILSVRC 2014 competition. It also be used one deeper and wider Inception network with slightly superior quality, but adding it to the ensemble seemed to improve the results only marginally. The details of that network are omitted, as empirical evidence suggests that the influence of the exact architectural parameters is relatively minor. The network was designed with computational efficiency and practicality in mind, so that inference can be run on individual devices including even those with limited computational resources, especially with low-memory footprint.
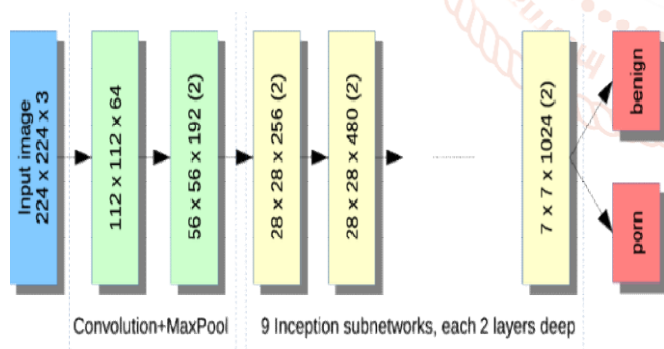

Figure1. GoogLeNet Structure

D. Training Methodology
GoogLeNet networks were trained using the DistBelief distributed machine learning system using modest amount of model and data-parallelism. Although we used a CPU based implementation only, a rough estimate suggests that the GoogLeNet network could be trained to convergence using few high-end GPUs within a week, the main limitation being the memory usage. Image sampling methods have changed substantially over the months leading to the competition, and already converged models were trained on with other options, some- times in conjunction with changed hyperparameters, such as dropout and the learning rate. Therefore, it is hard to give a definitive guidance to the most effective single way to train these networks.
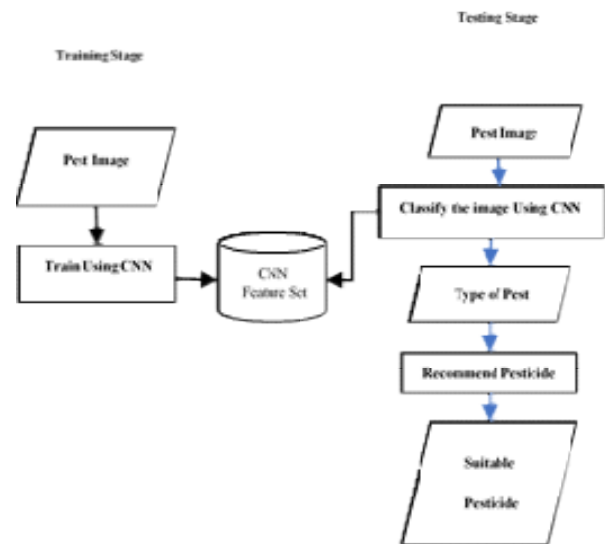
E. System Design

Figure2: System Design

F. Detail of the system
In first stage, training is performed and 1265 images are used as the training images. In the training process, firstly, the program takes the four types of pest images as the training data. Then, the training data is trained using Convolutional Neural Network model, GoogLeNet. Finally, the resulted features are stored in a CNN feature set.

In second stage, testing will be done. In the testing process, the user must input the test pest image. The user's input pest image will be classified by CNN and the system will give the result what kind of the pest. Lastly, the system will give the most probabilistic answer of which group the pest is belongs to and recommend the most suitable pesticide for it.

When the system gives the type of pest, four rules are used to emphasize this type of pest.

Rule:1
If   the type of pest is "hadda beetle"
Then   the Name is "Hadda Beetle"
And   the Family is "Coccinellidae"
And   the Scientific Name is "Henosepilachna vigintioctopunctata"
And   the Order is "Beetle"

Rule:2
If   the type of pest is "green stink bug"
Then   the Name is "Green Stink Bug"
And   the Family is "Pentatomidae"
And   the Scientific Name is "Chinavia hilaris"
And   the Order is "Hemiptera"

Rule:3
If   the type of pest is "looper"
Then   the Name is "Looper"
And   the Family is "Noctuidae"
And   the Scientific Name is "Trichoplusia ni"
And   the Order is "Lepidoptera"

Rule:4
If   the type of pest is "black cutworm"
Then   the Name is "Black Cutworm"
And   the Family is "Noctuidae"
And   the Scientific Name is "Agrotis ipsilon"
And   the Order is "Lepidoptera"

G. System Implementation

Figure3: Welcome Page

Figure4: Process for 'Start' button

When the user clicks the 'Start' button, the pests' information will appear as shown in figure 4.

The user will see the facts of the pests that damage the crops and plants. When the user clicks the button of 'လိပ်ခုံးကင်း (hadda beetle)', the damage signature and life cycle of this hadda beetle will be displayed as shown in figure 5. When the user clicks the button of 'ထြေကာင့်စိမ်း (looper)', the damage signature and life cycle of this looper will be displayed as shown in figure 6. When the user clicks the button of 'ပျူဖတ့ပိုး(black cutworm)', the damage signature and life cycle of this black cutworm will be displayed as shown in figure 7. When the user clicks the button of 'ဂိပိုးစိမ်း (green stink bug)', the damage signature and life cycle of this green stink bug will be displayed as shown in figure 8.
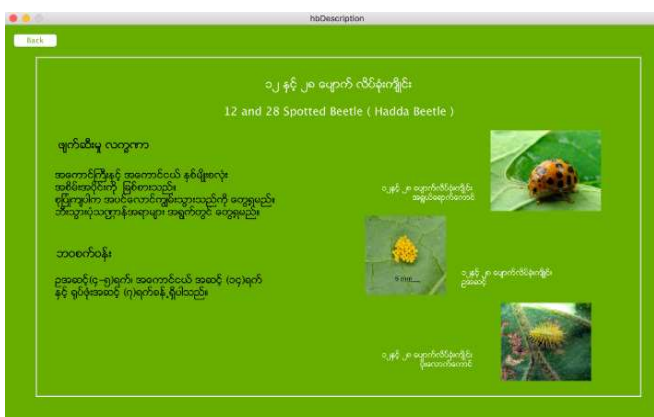

Figure5: Knowledge page for hadda beetle

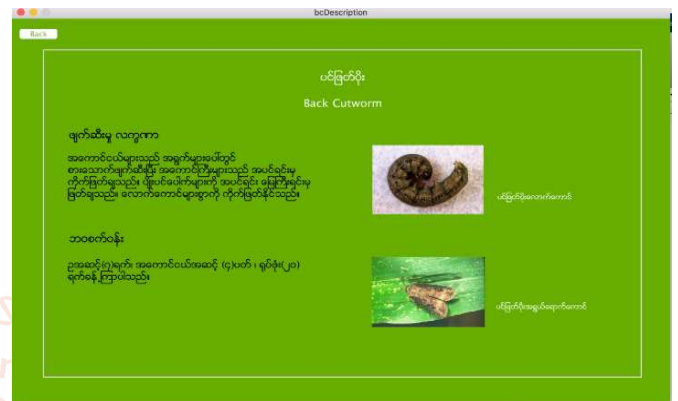**Figure6: Knowledge page for looper**

Figure7: Knowledge page for black cutworm

Figure8: Knowledge page for green stink bug

If the user chooses the image of 'Green Stink Bug' as an input and clicks 'Classify Process', the system will classify the type of pest as Green Stink Bug and display Name of this pest, Family Name of this pest, Scientific Name and Order.

Figure 9: Classification Process for green stink bug

If the user clicks 'Instruction' button, the respective instruction for the pests will be appeared as shown in figure 10.
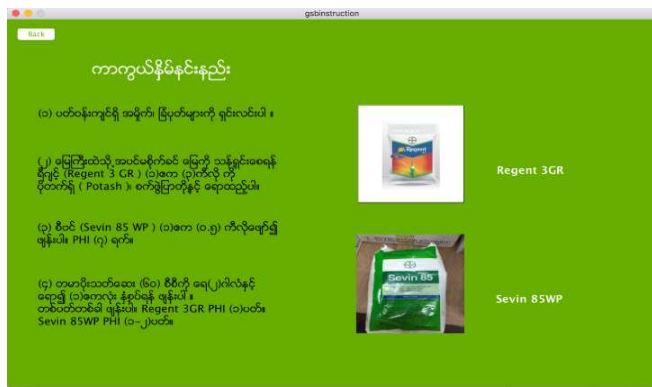
Figure10: Instruction page for green stink bug

If the user chooses the image of 'looper' as an input and clicks 'Classify Process', the system will classify the type of pest as Green Stink Bug and display Name of this pest, Family Name of this pest, Scientific Name and Order.

Figure11: Classification Process for looper

If the user clicks 'Instruction' button, the respective instruction for the pests will be appeared as shown in figure 12.

Figure 12: Instruction page for looper

If the user chooses the image of 'black cutworm' as an input and clicks 'Classify Process', the system will classify the type of pest as Green Stink Bug and display Name of this pest, Family Name of this pest, Scientific Name and Order.

Figure13: Classification Process for black cutworm

If the user clicks 'Instruction' button, the respective instruction for the pests will be appeared as shown in figure 14.

Figure14: Instruction page for black cutworm

If the user chooses the image of 'hadda beetle' as an input and clicks 'Classify Process', the system will classify the type of pest as Green Stink Bug and display Name of this pest, Family Name of this pest, Scientific Name and Order.
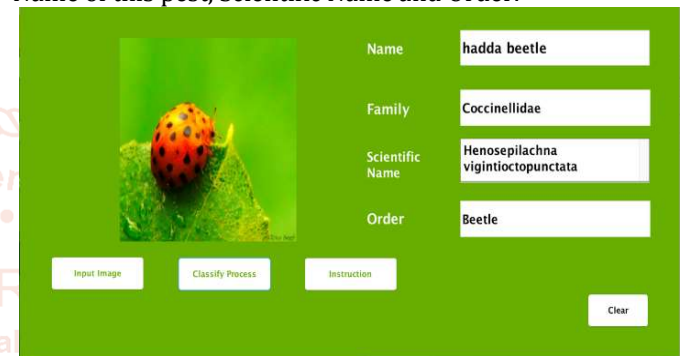
Figure15: Classification Process for hadda beetle

If the user clicks 'Instruction' button, the respective instruction for the pests will be appeared as shown in figure 16.
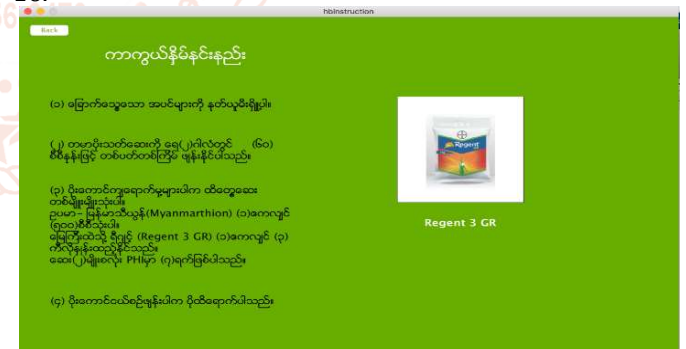
Figure16: Instruction page for hadda beetle

H. Conclusion

Pest recognition and pesticide recommendation can play an essential role in agriculture to help farmers, to know information of pests and pesticides which should be used. The user can get knowledge about the type of pest in agriculture and pesticide for this pest. The user inputs test image is classified and recognized which type of pest it is by using CNN classifier. And then, by using rules-based method, the suitable pesticide according to the type of pest is recommended. The failure to recognize/verify an image was due to poor image quality and high similarity between four pests. This system is implemented with Mat lab programming.

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